



**Faculty of Electrical and Electronic Engineering Technology**



**WIFI-BASED INDOOR LOCALIZATION UTILIZING MACHINE  
LEARNING TECHNIQUE**

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**Bachelor of Electronics Engineering Technology (Telecommunications)  
with Honours**

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**WIFI-BASED INDOOR LOCALIZATION UTILIZING MACHINE LEARNING  
TECHNIQUE**

**MUHAMAD AKMAL BIN RAZALI**

**A project report submitted  
in partial fulfillment of the requirements for the degree of  
Bachelor of Electronics Engineering Technology (Telecommunications)  
with Honours**



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## DECLARATION

I declare that this project report entitled “WIFI-BASED INDOOR LOCALIZATION UTILIZING MACHINE LEARNING TECHNIQUE” is the result of my own research except as cited in the references. The project report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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## APPROVAL

I approve that this Bachelor Degree Project 1 (PSM1) report entitled “WIFI-BASED INDOOR LOCALIZATION UTILIZING MACHINE LEARNING TECHNIQUE” is sufficient for submission.

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## DEDICATION

Alhamdulillah, praise to the Almighty Allah S.W.T

This thesis is dedicated to:

My beloved Parents,

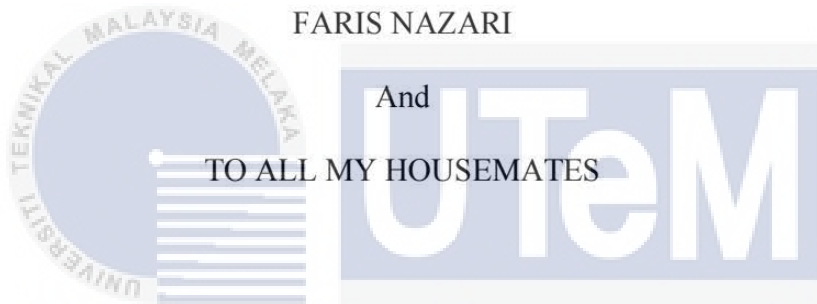
MR RAZALI and MRS SAMSIAH

*My supportive friends,*

FARIS NAZARI

And

TO ALL MY HOUSEMATES



اونيورسيتي تيكنيكل مليسيا ملاك

*My lovely and kindhearted Supervisor,*

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Ts. ZAHARIAH BINTI MANAP

## ABSTRACT

Position estimation using global positioning systems (GPS) is not reliable in indoor environment due to weak signal penetration and the complex nature of indoor setting which causes severe signal attenuation. This project will explore the potential of utilising available wireless signal in indoor environment which is WiFi. We will implement fingerprinting technique to predict the position of mobile devices in a confined indoor space. The methodology involves two stages which are training stage and testing stage. In training stage, sufficient number of data will be measured in a study area. The data will be the received signal strength (RSS) measured by a mobile phone at predetermined reference points (RPs). The measured data will be trained using machine learning technique in Matlab platform to produce an indoor localization prediction model. In the testing stage, the produced model will be used to predict the location of mobile devices based on measured RSS. This project is expected to compare the accuracy produced by several machine learning techniques, and identify the best prediction model to be used in WiFi-based indoor localization.

## ***ABSTRAK***

Anggaran kedudukan menggunakan sistem penentududukan global (GPS) tidak boleh dipercayai dalam persekitaran dalaman disebabkan oleh penembusan isyarat yang lemah dan sifat tetapan dalaman yang kompleks yang menyebabkan pengecilan isyarat yang teruk. Projek ini akan meneroka potensi menggunakan isyarat wayarles yang tersedia dalam persekitaran dalaman iaitu WiFi. Kami akan melaksanakan teknik cap jari untuk meramalkan kedudukan peranti mudah alih dalam ruang tertutup terkurung. Metodologi melibatkan dua peringkat iaitu peringkat latihan dan peringkat ujian. Dalam peringkat latihan, bilangan data yang mencukupi akan diukur di kawasan kajian. Data tersebut akan menjadi kekuatan isyarat diterima (RSS) yang diukur oleh telefon mudah alih pada titik rujukan (RPs) yang telah ditetapkan. Data yang diukur akan dilatih menggunakan teknik pembelajaran mesin dalam platform Matlab untuk menghasilkan model ramalan penyetempatan dalaman. Dalam peringkat ujian, model yang dihasilkan akan digunakan untuk meramalkan lokasi peranti mudah alih berdasarkan RSS diukur serta-merta. Projek ini dijangka membandingkan ketepatan yang dihasilkan oleh beberapa teknik pembelajaran mesin, dan mengenal pasti model ramalan terbaik untuk digunakan dalam penyetempatan dalaman berasaskan WiFi.

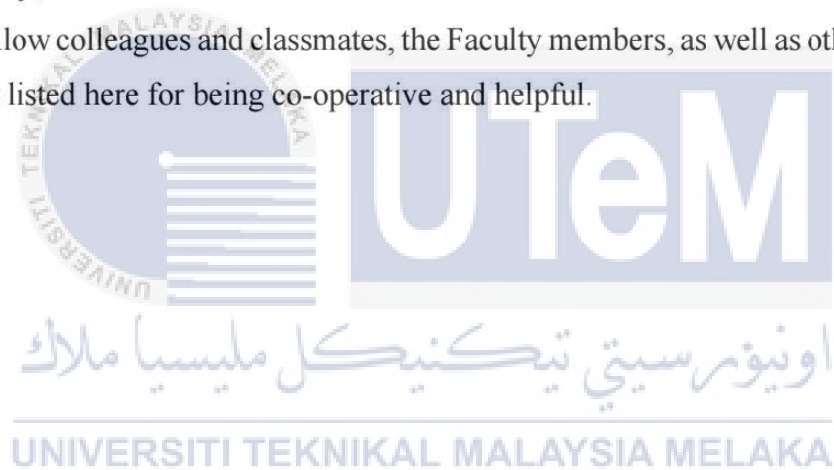


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## LIST OF SYMBOLS



## LIST OF ABBREVIATIONS



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# CHAPTER 1

## INTRODUCTION

### 1.1 Background

There are numerous outdoor positioning systems available, including GPS, A-GPS, Galileo, and others. However, they are only available outside and cannot give the accuracy required for indoor location. GPS, for instance, has a maximum accuracy of 5 metres. An accurate precision that is inappropriate for interior spaces. Outdoor accuracy can be accomplished using the Global Positioning System (GPS), but indoor performance is limited due to insufficient signal levels. Indoor localization has been proposed using a variety of technologies, including magnetic fields, Bluetooth, and WiFi. WiFi has the best availability and accuracy of all of them. Because of this, accurate localization is available in practically any setting and on almost any device. However, WiFi-based localization remains a challenge.

The WiFi-based location accuracy is calculated by measuring the distances between the mobile phone and the accessible Access Points (APs). The Received Signal Strength Indicator (RSSI) is used to figure out how far WiFi-based location estimate has to go. Many strategies for localization have been developed based on the RSSI, which are split into two broad categories signal propagation models and fingerprinting methodologies. Because of the random propagation effects, using the path loss propagation model in indoor environments makes distance estimate impossible, necessitating the use of multiple models in different regions. In interior situations, the fingerprint technique is extensively used due to its resilience and inexpensive cost.

This project will look into the possibility of using WiFi as a wireless signal in an indoor context. In a constrained indoor setting, we will use a fingerprinting technique to forecast the location of mobile devices. The training stage and the testing stage are the two steps of the process. A sufficient number of data will be measured in a study region during the training stage. The data will be received signal strength (RSS), which will be measured by a mobile phone at predefined reference points (RPs). To create an indoor localization prediction model, the measured data will be trained using machine learning techniques in the Matlab platform. In this project, we only consider line-of-sight (LoS) conditions where there is no blockage between the mobile phone (target) and the WiFi access points (APs). The methods are based on regression models which provide a smooth position prediction.

## 1.2 Problem Statement

Outdoor positioning accuracy can be accomplished using the GPS that can provide an positioning error of about 5 metres. However, indoor positioning systems can't rely on GPS due to high signal penetration loss that reduce the positioning performance. Indoor localization has been proposed using a variety of technologies, including magnetic fields, Bluetooth, and WiFi. WiFi has the best availability and accuracy of all of them. Because of this, accurate localization is available in practically any setting and on almost any device. However, WiFi-based localization remains a challenge mainly due to rapid fluctuation in RSS. This problem causes error in measuring the distances between the mobile phone and the accessible APs.

Many strategies for localization have been developed based on the RSSI, which are split into two broad categories signal propagation models and fingerprinting methodologies. Because of the random propagation effects, using the path loss

propagation model in indoor environments makes distance estimate impossible, necessitating the use of multiple models in different regions. Therefore, in this project, we will implement fingerprinting technique which is more resilience and inexpensive cost. We will trained the measured data to obtain the best localization prediction model with the highest accuracy.

### 1.3 Project Objective

The aim of this project is to:

1. To develop a fingerprints reference database through manual measurement of received signal strength (RSS) by using mobile application.
2. To develop an indoor localization model for specific scenario by using machine learning techniques.
3. To evaluate the performance of the developed indoor localization model.

### 1.4 Scope of Project

The scope of this project are as follows:

1. The proposed project were tested in a Double Storey House but only conducted on 1st Floor .

2. There were four available WiFi Access Points (APs) located in the house .
3. A floor map was created based on the 1st Floor of the House that being tested and the WiFi Access Points (APs) located in the floor.
4. An android application was used on a mobile device. The application was used to collect RSS measurements from the available Access Points (APs) .
5. The radio map is created using the Receive Signal Strength (RSS) readings that have been obtained.
6. We consider line-of-sight (LOS) scenario where the mobile phone (mobile device) and WiFi access points (Aps) are not blocked.



## CHAPTER 2

### LITERATURE REVIEW

#### 2.1 Introduction

Due to weak signal penetration and the complex structure of indoor settings, which causes severe signal attenuation, position estimation using GPS is not reliable in an indoor context. This project will look into the possibility of using the available WiFi signal in an interior context. In a constrained indoor setting, we will use fingerprinting to forecast the location of mobile devices. The training and testing stages are both included in the system.

A sufficient number of data will be measured in a study region during the training stage. The data will be received signal strength (RSS), which will be measured by a mobile phone at predefined reference points (RPs). To create an indoor localization prediction model, the measured data will be trained using machine learning techniques in the Matlab platform. The developed model will be utilised in the testing stage to forecast the position of mobile devices based on real-time RSS measurements. The goal of this research is to assess the accuracy of several machine learning approaches and determine the optimal prediction model for WiFi-based indoor localisation.

#### 2.2 Overview of Localization System

Indoor localization system technologies could be a forward-thinking invention, similar to how the Global Positioning System (GPS) revolutionised outdoor navigation. According to the authors (Michael Brown and James Pinchin, 2013), no single indoor localization technology available today can give an absolute solution for every indoor

localization case. However, a variety of technologies are being offered as a means of developing and improving the indoor localization system.

A detail survey on indoor localization system can be found in [1]. The authors described the technologies, techniques and algorithms used for indoor localization system. The most common and widely used technologies as mentioned in the articles are Satellite, Ultra-wideband (UWB), Wi-Fi, ZigBee and Bluetooth. Table 2.1 illustrates the comparison between technologies used in IPS which done by authors in [1].

Table 2-1: Comparison between technologies used Indoor Localization

Technology	Cost	Coverage	Advantages	Disadvantages
Satellite		Floor level	Low power consumption	-
Ultrasonic Based	Medium-High	Room level	-Good accuracy -No effect of multipath -Cheap	-Interference -Cost for hardware
Infrared	Medium	Room level (few meters)	-Cheap -No effect of multipath -Low power consumption	-Sunlight interference -Short-range -Cost for hardware
Visible Light	Medium	Floor level	No interfering	Expensive construction
Wi-fi	Low	Floor level (around 35)	-Good Accuracy -Low cost -Signals can penetrate walls	-RF interference with devices operating at 2.4 GHz -Fingerprinting requires a huge effort
Zigbee	Medium	Floor level	-Low cost -Low power consumption	-Require special equipment

Bluetooth	Low-Medium	Floor level (around 10)	-Good accuracy -No need for additional infrastructure -Low power consumption	-RF interference -Limited coverage and mobility
Inertial	Low	Floor level	Cheap	-Accumulative errors
Magnetic Based	Low	Floor level	Cheap	Requires mapping

Based on all technologies above, Wi-Fi does not demand any additional hardware or infrastructure. Wi-Fi infrastructure is already available in nearly all locations, offering a basic level of positioning capability without additional investment. Manually deployed hardware solutions can be expensive and time intensive, especially if you have many sites that require the capacity. As a result, other technologies need a bigger financial and time investment in order to establish an effective indoor localization environment.



### 2.2.1 Technologies for Indoor Localization

Interior localization systems are classed according to how they determine their most common technology for locating indoor surroundings. Radio frequency (RF), inertial, audible and non-audible sound, light-based, and vision-based technologies are commonly used.